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Feeling Alone Among 317 Million Others: Disclosures of Loneliness on Twitter

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Abstract

Increasing numbers of individuals describe themselves as feeling lonely, regardless of age, gender or geographic location. This article investigates how social media users self-disclose feelings of loneliness, and how they seek and provide support to each other. Motivated by related studies in this area, a dataset of 22,477 Twitter posts sent over a one-week period was analyzed using both qualitative and quantitative methods. Through a thematic analysis, we demonstrate that self-disclosure of perceived loneliness takes a variety of forms, from simple statements of *"I'm lonely"*, through to detailed self-reflections of the underlying causes of loneliness. The analysis also reveals forms of online support provided to those who are feeling lonely. Further, we conducted a quantitative linguistic content analysis of the dataset which revealed patterns in the data, including that 'lonely' tweets were significantly more negative than those in a control sample, with levels of negativity fluctuating throughout the week and posts sent at night being more negative than those sent in the daytime.

Keywords

Twitter; loneliness; self-disclosure; social media.

Feeling Alone Among 317 Million Others: Disclosures of Loneliness on Twitter

1. Introduction

Recent reports (British Red Cross, 2016; Office for National Statistics, 2018a, 2018b) have highlighted the alarming levels of loneliness experienced by individuals across the globe (McPherson et al., 2006) and across all age groups (Griffin, 2010; Office for National Statistics, 2018a), with documented potential impacts on individuals' health (S. Cacioppo et al., 2014; Eichstaedt et al., 2015; Holt-Lunstad et al., 2015, 2010). Given the ubiquitous nature of technology, unsurprisingly there has been a great deal of attention on the potential relationship between technology and issues such as loneliness (Nowland et al., 2018). Extant research that considers the relationship between feelings of loneliness and the use of technology can usually be placed into one of two broad categories: those that consider the role of technology in potentially causing or exacerbating feelings of loneliness (e.g. (Holt-Lunstad et al., 2010; Martončik & Lokša, 2016), and those that consider how technology might be used to prevent loneliness or help individuals to cope and seek support (Kivran-swaine et al., 2014; Naslund et al., 2016). Indeed, some studies have gone so far as to suggest that Facebook use is linked to increased satisfaction with life in certain populations (Basilisco & Cha, 2015). The need for further research in this area has also been highlighted (Anderson et al., 2012; Singleton et al., 2016) in the light of the continuing growth and development of social media sites. The focus thus far has been on specific countries, with previous studies suggesting interesting findings in their data – such as temporality, but not exploring it fully within their own analyses.

Social media sites, such as Twitter, have been identified as affording particular qualities that enable people with both transient and enduring feelings of loneliness to express themselves and receive reassurance from others (Kivran-swaine et al., 2014). Our work approaches Twitter from the theoretical perspective that social networking services (SNSs) collectively represent a socio-technical space, which is shaped by the individual platform affordances. This is broadly aligned with MacKenzie & Wajcman (1999), who assert that "*social shaping*" not only underpins the development of new technologies, but shapes their use "*as inextricably part of society*". Within online research, Hine (2015, 2017) asserts there has been a cultural shift which has firmly embedded online activity as part of the everyday, in all aspects of life, with Pink (2012) framing this as '*digital everyday normality*'. As a result of the increasing socially normative use of Twitter, tweets within this work are treated as mediated communication as part of an everyday practice of use. This places the support seeking behaviors and support derived from online interaction on Twitter as both potentially effective and having a significant potential for efficacy in interactions, where offline support structures are perceived as poor or absent for individuals. For large scale social phenomenon, this positions Twitter data as having significant use in the exploration of loneliness and isolation. Rather than seek to determine whether Twitter use causes, exacerbates, or alleviates feelings of loneliness, this article presents an investigation into the contemporary self-disclosure of loneliness on Twitter. Our work extends this existing understanding to examine, in further detail, the patterns that are present in disclosure related to the time and day that posts were originally sent, and the seeking and provision of support.

We posit the following questions, which we seek to address within this article.

RQ 1. What topics are typically discussed on Twitter, regarding loneliness?

RQ 2. How is Twitter used in the seeking and provision of supporting regarding loneliness?

RQ 3. When discussing feeling of loneliness, how does the language used by social media users differ from posts regarding other topics?

RQ 4. How, and to what extent, does the time and day that posts are shared have an impact on the language used within them?

a. To what extent do 'lonely' posts sent at the weekend differ from those sent during the week?

b. To what extent do 'lonely' posts sent at night differ from those sent during the day?

To address these questions, we collected a dataset of 22,477 Twitter posts over a period of one week. To analyze this data we combine a qualitative analysis of the tweet content, and a quantitative linguistic content analysis. In doing so, we seek to highlight nuances and patterns apparent within the disclosure of loneliness, as well as changes in the use of language within and across the days.

The findings from our study offer a number of contributions to the emerging discourse on loneliness and technology. First, we offer a deepened understanding of how social media users disclose and discuss feelings of loneliness through these sites. Second, we note the importance of temporality in usage behavior patterns, noting differences in relation to both the day of the week, and time of day that users share their experiences of loneliness. Third, we highlight the wide-ranging audiences that these platforms provide to people who experience loneliness, and how this provides a support network for those who explicitly express these feelings. Finally, we make suggestions for areas of future work, building on the findings of this study.

2. Related Work

Loneliness may stem from the lack of an immediate other, or low participation within social groups, with (Perlman & Peplau, 1981) defining loneliness as "*...the unpleasant experience* *that occurs when a person's network of social relations is deficient in some important way*". Frequently described as a social phenomenon, loneliness is closely aligned, or indeed directly linked, with negative health outcomes (S. Cacioppo et al., 2014; Eichstaedt et al., 2015; Holt-Lunstad et al., 2010, 2015). It is therefore important to explore the experiences of people who self-disclose that they are lonely as this can offer insights into how to understand, manage and mitigate against these experiences. In recent years, researchers have demonstrated the ways in which social media platforms may act as a site for the disclosure of personal information, with research focusing, for example, on areas such as political expression (Haridakis et al., 2017; Mahoney et al., 2016), health and wellbeing (De Choudhury, Counts, et al., 2013; De Choudhury, Gamon, et al., 2013; Jamison-Powell et al., 2012; Scanfeld et al., 2010; Walther et al., 2016), as well as the more mundane aspects of everyday life (Hu et al., 2014; Le Moignan et al., 2017). In the context of health, disclosure on social media not only represents an outlet for individuals seeking support (Walther et al., 2016) but may also provide valuable information for public health purposes such as identifying the spread of flu-like symptoms (Paul et al., 2014; Sadilek et al., 2012), identifying symptoms of depression (De Choudhury, Gamon, et al., 2013; Moreno et al., 2011; Park et al., 2012), and *infodemiology* – using such data in order to support and inform public health decisions and policies (Eichstaedt et al., 2015; Eysenbach, 2009). For example, Ranney et al. (2016) observed a statistically significant relationship between the number of alcohol-related tweets per hour from a given geographical area, and the number of alcohol-related visits to the emergency department in that area. They suggest that real-time monitoring of such content may help in predicting surges in the number of visitors to local emergency departments.

Self-disclosures may also be beneficial to the individuals concerned (Choi & Toma, 2014; Gable et al., 2004; Ma et al., 2016). Social psychology research highlights the benefits that the self-disclosure of worries, anxieties and negative experiences can have on an individual's mental and physical health (Chu et al., 2010; Pennebaker, 1997). In the context of loneliness, such benefits might also include increasing feelings of connectedness (Quinn & Oldmeadow, 2013) – a primary human need (Ryan & Deci, 2000) – and reducing the active mental work required by keeping such feelings to oneself (Lane & Wegner, 1995). Given that feelings of loneliness, by definition, imply the perceived unavailability of significant others to disclose to, social networking services like Twitter potentially become increasingly relevant as a space for individuals to disclose their feelings to others.

However, there are also inherent risks involved in self-disclosure. Sharing content of a personal nature online has associated risks, including loss of privacy which may increase vulnerability (Bazarova, 2012; Spottswood & Hancock, 2017). Additionally, there are issues of managing disclosure across multiple groups and audiences in an appropriate fashion (DiMicco & Millen, 2007). It is also possible that some users may come to regret their decision to share such information online. Wang et al. (2011), for example, provide a comprehensive summary of the types of regret experienced by Facebook users. These include negative audience response or causing offense, aligned with subsequent concerns over perceptions of self by others, posting in a state of heightened emotion, (termed a "hot state") or while in a state altered by alcohol or drug consumption, without regard for consequences. Additionally, regret of disclosure may stem from unintentional transgression of group social boundaries. Work in relation to Twitter (e.g. Sleeper et al., 2013) similarly identifies that heightened emotional states and tweets which are cathartic in nature can often lead the original author to regret posting those messages. Furthermore, Wang et al. (2014) highlights that Twitter networks can be comprised of diverse audience types, leading to '*context collapse*'. This is identified by Marwick & boyd (2011) as potentially problematic for users to navigate content sharing on a platform where multiple audience groups are present simultaneously, as content may not be welcomed or deemed appropriate by all those present.

Whilst disclosure of a personal nature can thus lead to regret, it can also impact the 'success' of individual Twitter account holders. Hutto et al. (2013) demonstrate, in a longitudinal study, that accounts which contain a higher proportion of negative content have a reduced rate of follower gain compared to those which share positive content, which is associated with higher rates of follower gain. This is indicative that as a social platform, audience responses to disclosure may be influenced by the regularity or severity of the disclosure of an individual's feelings of negativity, social isolation or loneliness. At the same time, however, sharing behaviors on social media platforms are often shaped by the expectation that content will be read by followers, ultimately provoking some form of engagement. In studying this dynamic, in contrast to Hutto et al's work, Bernstein et al. (2013) suggest that users display an awareness of the "imagined audience" when formulating tweets and as a result they often self-moderate the content they share.

In a study closely related to our own, Kivran-swaine et al. (2014) studied disclosures of loneliness on Twitter. Deriving their search criteria from previously published expressions of perceived social isolation (Russell et al., 1978), they used these complete phrases as search terms with the Twitter Search API, though they acknowledged that this may well have excluded other expressions of loneliness. As part of their analysis, posts were qualitatively analyzed with three main categorical dimensions being highlighted: the context of loneliness, the temporal bounding of the loneliness, and the interaction (or lack of interaction) with others.

This notion of temporality, and its importance, is not a new phenomenon when studying loneliness, Young (1982) emphasizes that feelings of transient loneliness (as opposed to enduring or chronic loneliness) emerge and die out quickly. Further to this, in relation to social media, De Choudhury et al. (2013) state that "*patterns of posting…bear the potential to offer evidence as to how a person is affected by life events*". Social media users often share posts as a 'stream of consciousness', sharing experiences as events are happening, or they are experiencing particular feelings (Wang et al., 2011). As such, it is feasible that social media users' online behavior may indeed be reflections of changes in the users' experiences, mental state, and life events in almost real-time. If so, it is important to understand this further, given that when individuals seek support or ask questions online, the timeliness of response is a key factor in individuals judging a response's quality (Cheung et al., 2008; Walther & Jang, 2012), and as such, adopting any advice or answers provided. Through a greater understanding of this behavior, effective support and intervention systems could be designed and implemented, with support available to those seeking it, when they are likely to need it.

As outlined previously, the focus of the study presented here is the self-disclosure of loneliness on social media, with particular reference to Twitter. Building on previous work, we note the importance of temporality when studying loneliness within our study, but extend this work through the consideration of when the expressions of loneliness occur – both in terms of the day of the week, and also the time of day that the posts were sent. While there is existing research in this area, such as Kivran-swaine et al. (2014), we seek to complement their earlier findings through the use of a broader search criterion, analyzing a dataset using both qualitative and quantitative approaches, and considering our results in relation to the day and time that the original posts were created.

3. Study Design & Data Analysis

This study sought to expand upon previous work by focusing on how disclosures of loneliness may differ based on the time of day, or day of the week in which they were shared. For example, one specific aim was to highlight if disclosures of loneliness were more prolific when individuals may be alone, or when they feel that society suggests that 'the norm' is to be spending time with friends – such as socializing at the weekend.

Through a combination of quantitative and qualitative methods, we were able to analyze and understand patterns of behavior within a large-scale dataset, while still developing an understanding of the nuances of the content of individual posts.

3.1. Data Collection

Using the Twitter Search API (Twitter, 2018), a total of 22,477 original tweets were collected over a 7-day period in May 2017 (retweets were ignored at the collection stage) based on a query of the search term 'lonely'. Only public tweets are made accessible through the Twitter API, while tweets sent from private, or otherwise restricted accounts, are not shown in search results. While previous research, such as Kivran-swaine et al. (2014), collected specific phrases such as 'I'm so lonely' and 'I feel left out', we elected to collect tweets that contained a single word. In doing so, we sought to collect and characterise a wider range of loneliness self-disclosures. The resulting dataset will be referred to as the "lonely tweets" dataset hereafter. Table 1 shows the number of tweets collected per day, as well as in each timeframe. As Twitter provides the user's time zone, and the 'offset' in relation to the UTC timestamp, it is possible to make adjustments so that the days and times reflect the local time in which the tweet was posted. This allows for a more accurate comparison between the time and days that tweets were initially posted.

3.2. Qualitative Analysis of Tweets

Qualitative analysis of Twitter content allows for a deeper understanding of the material being shared – particularly in cases where the context is nuanced, sarcastic, colloquial, or abbreviated to meet the character limit imposed by Twitter. However, an analysis of the full dataset would be highly resource intensive, and as such, following practice in the related past literature (e.g. Brooker et al., 2015; Jamison-Powell et al., 2012; Johansson & Andreasson, 2017), a subset of data was chosen for in-depth analysis. A randomly selected subset of tweets was selected, with each of the time blocks for each day, i.e. Thursday 4-8pm, proportionally represented (1 in 25 tweets for each time slot were selected). This was done as to ensure fair representation of the data sample across the entire collection period and resulted in a representative sample of 804 tweets.

3.3. Data Analysis

The 804 tweets were analysed using the method described in (Braun & Clarke, 2013), using two independent coders. The 804 tweets were initially read by one researcher several times, with notes made where appropriate. Following this, an initial list of codes that summarised individual tweets was generated, and revisited, revising where appropriate. In order to facilitate the remainder of the analysis, an initial codebook was created, which included the applied codes, a description of each code, along with examples of tweets for each code. Two researchers then considered the codebook; after discussion between the researchers, the codebook was revised and refined where necessary, leaving a final list of 23 codes (see Table 2, right column). At this point it was necessary to assess the reliability of the codes within the wider dataset, so a second subset of tweets, consisting of the 35th tweet in each day and time block was selected, resulting in a further set of 575 tweets for analysis. The researchers then independently applied the codes to the second subset of tweets. The use of codes was then examined for inter-rater reliability using Cohens' Kappa, producing a result of $\kappa = 0.804$ indicating a significant level of agreement (Landis & Koch, 1977).

As a final step in the analysis, all of the codes were examined once again to identify common themes across codes. This led to the formation of seven first-order themes. Following further examination and synthesis of the data, these first-order themes were collapsed into three second-order themes. Of these three second-order themes, two are relevant for the purposes of this particular study ("Loneliness and Self", and "Loneliness and Others"). Tweets falling within themes deemed to be irrelevant to the focus of this study will not be explored or detailed extensively within this article. Table 2 shows the relationship between the first-order and second-order themes, and the codes used during the initial analysis of the data.

4. Results of Qualitative Analysis

Here we outline the results of our qualitative analysis. We divide our analysis into the two relevant second-order themes and their five first-order themes.

4.1. Second Order Theme 1: Loneliness and Self

Within this second-order theme, there are three first-order themes: 'Personal Disclosure', 'Fear and the Unknown', and 'Reflecting on Loneliness'. Tweets that have been grouped within these themes demonstrate the social media user reflecting on their own experience of loneliness, be that disclosing that they are lonely, sharing their fear of being lonely in the future or reflecting on loneliness in general.

Personal Disclosure: Tweets within this theme include those where the author is disclosing their own personal experience of loneliness – be that a past or present, constant or intermittent feeling. This theme also includes tweets where the author is disclosing that they do not feel lonely. Those pertaining to a current state were observed to be brief statements without additional detail, such as *"lonely as f"*, *"Lonely and sad"* and "*Nights are lonely and so are the days."*. This short style of disclosure was also observed in tweets which specifically described a constant feeling of loneliness, with the permanent nature of the feeling adjoined to the simple disclosures found in current state disclosure; *"I am lonely all of the time"* or *"I always feel that I am lonely"*.

Within this theme, there is a wide array of degrees of personal disclosure, from short and simple statements of *"I'm lonely"*, through to more detailed accounts of how individuals are spending a vast majority of their time using social media, as means of supplementing their *"…lack of any actual meaningful human connection"*.

Fear and the Unknown: This content relates to self-disclosure of a potential future state, rather than disclosing feelings of loneliness that have been, or are being, experienced. As such, this content may reflect individuals attempting to receive support or guidance before they feel lonely, rather than during or after feelings of loneliness. These included statements overtly referencing fear such as *"Scared to be lonely".* These were not limited to singular statements on behalf of an individual, with collective fear also referenced in *"we are all scared to be lonely".*

Reflecting on Loneliness: Within this theme, the content of tweets focuses on personal reflections on loneliness – be that the author's own specific experiences (e.g. "*Everyone I graduated with is either engaged, pregnant, or giving birth and I'm over here alone and lonely*"), or more general reflections on loneliness (e.g.*"Being what you call lonely is viewed as something negative, or less healthy but I disagree. Its liberating"*).

Some of these tweets equate loneliness with being single, suggesting that being in a relationship and having a partner would end or reduce their feelings of loneliness. This may highlight the cultural weight placed upon romantic attachment, examples of such content includes: *"…my boyfriend goes to sleep early and I start to feel lonely because he's the only one I talk to",* and *"Couples always disgust me, they remind me of how lonely I am".*

Similarly, others relate their loneliness to a temporary absence of partners, family members or close friends as well as a lack of emotional connection to those around them: *"it is so easy to be surrounded by people and yet still feel lonely"* and "*The very worst kind of being lonely is when no one truly sees you for who you really are".*

Rather than merely sharing that they are lonely, tweets within this theme demonstrate that Twitter users are using the platform as a means of reflecting on their own loneliness and sharing these reflections with a wider audience. These reflections have the potential to be of benefit to both the author (Pennebaker, 1997; Pennebaker et al., 2015) and also others who are reading the posts and who may also be suffering from feelings of loneliness (Bazarova, 2012). It is also possible that these posts could have a negative impact on the author, in particular in situations where the author is hoping for, or expecting, a response but does not receive one. There is also evidence of displacement using humour to express loneliness in a less overt manner, with tweets such as *"I'm not saying that I'm lonely, but I did spend the last 15 minutes having a conversation with the wall"* and *"Owning a car with four doors makes me feel lonely lol"*.

4.2. Second Order Theme 2: Loneliness and Others

Within this second-order theme, there are two related first-order themes: 'Direct Support' and 'Indirect Support and Information Dissemination'. Tweets that have been grouped within these two themes represent social media users utilising these technologies to provide support, in some form, to other users of the platform that may be feeling lonely.

Direct Support: Tweets within this theme include those where there is evidence of social media users providing direct support to others that may be suffering from feelings of loneliness. There are many potential benefits to such support mechanisms, not only for those being supported, but also for those providing support.

Examples of this direct support include content such as "*@user I won't feel lonely. I won't feel lonely. I won't feel lonely. #positiveAffirmations*". Others seek to demonstrate that feeling lonely is not unusual, and that many people go through periods of feeling lonely, such as *"@user It's ok, we understand. Feeling lonely is just a normal part of life. *hug*"*. While both of these examples demonstrate the direct support that is being provided to other users, they also serve to demonstrate the subtle variations in how this support may be provided.

This support may take the form of 'reciprocal self-disclosure' (Pan et al., 2018), where individuals are sharing their own experiences of loneliness as a means of supporting others – benefitting not only the person they are supporting (Bazarova, 2012), but also themselves

(Pennebaker, 1997; Pennebaker et al., 2015), for example: *"@user I feel the same, nobody wants to hangout with me, which makes me depressed and lonely"*. In this post, the replying user is not only providing support, but also disclosing their own experience of loneliness at the same time.

This direct interaction between social media users, which might be considered as a form of support network, may also lead to an increased feeling of connectedness between those that are interacting. Described as a primary human need (Johansson & Andreasson, 2017; Ryan & Deci, 2000), this potential for an increased feeling of connectedness would be a further benefit for those discussing feelings of loneliness, as well as the more immediate support gained from other social media users.

Indirect Support and Information Dissemination: Tweets included within this theme include those that are sharing information and facts regarding loneliness, or may include quotes that relate to being, or feeling, lonely.

These tweets may represent an effort to indirectly support those that may be feeling lonely, as well as raising awareness with other social media users about loneliness and surrounding issues. Such tweets often include reference to recent research, or case studies, that highlight the extent of this loneliness 'epidemic': *"Psychologists have found that sending and receiving text messages can actually boost your mood when you're feeling lonely"*. Whilst not being directed at any particular user, such posts may provide indirect support to individuals, as they are shown that they are not the only ones that may be feeling lonely or are provided with links to external resources that may be relevant to them, such as studies and other support platforms and resources.

5. Quantitative Linguistic Content Analysis

As noted earlier, with a collected dataset of 22,477 tweets, a qualitative analysis of the entire dataset would be impractical. As such, tools such as Linguistic Inquiry and Word Count

(LiWC) (Pennebaker et al., 2015) provide a suitable means for analysing such large datasets. LiWC *"…reads a given text and counts the percentage of words that reflect different emotions, thinking styles, social concerns, and even parts of speech.*" (Pennebaker et al., 2015). However, in order to better understand how specific these findings are to the loneliness tweets dataset, we also analysed a dataset which consisted of randomly collected tweets. This dataset, referred to as the 'random sample' hereafter, was collected from the Twitter Streaming API, sampled evenly over the 7-day period, resulting in a comparable dataset of 21,105 tweets. Collecting this random sample allows comparisons to be made between the two datasets and will highlight differences between tweets where individuals express feelings of loneliness, and tweets that represent a more generic use of the platform. In doing so, we further build on the work of Kivran-swaine et al. (2014).

In the sections that follow, we outline our analysis methods, before discussing the results of this analysis, their relation to other research and their broader implications.

5.1. Data Analysis

The content of tweets included in the lonely tweets dataset was analysed using LiWC (Pennebaker et al., 2015). Results generated by this software indicate the percentage of the analysed text that contains particular classes of words. Such classes include demonstrations of negative and positive emotion, anger, sadness and anxiety, as well as past, present and future tenses (see Table 3). Independent t-tests were deemed to be appropriate for comparing results between the two datasets (Lumley et al., 2002).

To provide a greater level of detail, the lonely tweets dataset was further broken down, and analysed in terms of the day of the week when the tweet was sent (see Table 4), as well as the time of day (see Table 5). As discussed earlier, the Twitter API provides the UTC timestamp of when the tweet was created, as well as an 'offset' value, determined by the user's time zone. This allowed for the analysis to be based on the presumed local time when the tweet was sent. Table 1 shows the number of collected tweets, based on the date they were sent, as well as the time of day they were posted.

To test for differences between the two datasets, content analyses were conducted using LiWC (Pennebaker et al., 2015). The use of pronouns – both personal and impersonal, as well as verbs and auxiliary verbs was compared between the two datasets. Further to the word classes detailed above, a sentiment analysis was carried out – detailing the use of words demonstrating a positive or negative sentiment. Finally, the use of tense and the utterance of temporality within the tweets was analysed – LiWC also reports on the use of the past, present and future tenses in the analysed texts.

5.2. Comparison to Random Dataset

Detailed in Table 3, statistically significant differences are demonstrated across each of the root word classes ($p < .001$), with each word class being more prevalent in the lonely tweets dataset than the random dataset. Further, the lonely tweets dataset contained a statistically significant ($p < .001$) and higher prevalence of negative words when compared to the random sample dataset. When comparing the prevalence of positive word use between the two datasets, there was no significant difference between the two collected datasets.

There are well documented links between loneliness and health – both physical (e.g. (Holt-Lunstad et al., 2015, 2010) and mental (e.g. J. T. Cacioppo et al., 2006). In order to determine the extent to which disclosure of loneliness on social media might also include these aspects, we analysed the use of the following word roots as defined by LiWC (Pennebaker et al., 2015): ‘health’, ‘feeling’, ‘anger’, ‘sadness’, and ‘anxious’. As demonstrated in Table 3, there is a significant ($p < .001$) difference between the two datasets, with the lonely tweets dataset including a higher rate of use than the random sample. Whilst other word categories contributed to the overall negativity expressed within the tweets, the level of expression of sadness is similar to the presence of negative sentiment.

The greater use of the present tense in the lonely tweets compared to the random tweets highlights that users are more likely to be sharing their emotional state in, perhaps, almost real time. This might reduce the level of self-moderating (Bernstein et al., 2013) that occurs, which in turn could cause feelings of regret (Kaur et al., 2016; Wang et al., 2011; Xie & Kang, 2015) if the user, on reflection, feels that they may have over-shared. Such disclosures could be defined as self-concept self-disclosures, which have been documented as encouraging higher levels of engagement in a support-seeking environment (Pan et al., 2018). This suggests that, rather than merely stating that they are lonely, social media users may be deliberately sharing more personal information and doing so in such a way that they are actively trying to seek support from others.

5.3. Variations by Day

In previous sections, we have noted statistically significant differences between the 'lonely tweets' dataset and the 'random dataset' – such as the length of the tweet, and the level of negativity expressed within the tweets. There are also notable differences within the lonely tweets dataset on a day-to-day basis.

Table 4 demonstrates, for example, that Monday is by far the 'angriest' day of the week (see also, Figure 1), with statistically significant differences between Monday and every other day, with p-values ranging from $p < .001$ (Thursday, Saturday) to $p = .019$ (Tuesday). Further, the expression of negative sentiment also differs over time, Table 4 shows that, on average, tweets sent on Saturday, Sunday or Monday (see also, Figure 2) demonstrated higher levels of negative sentiment than those sent in the rest of the week.

5.3.1. Variations between the weekend and weekdays

Table 4 also highlights a general trend for results to be noticeably different on a weekend compared to the rest of the week. Comparing tweets posted at the weekend (Saturday, Sunday) to the rest of the week highlights two difference in tweeting behaviour. First, users posting about loneliness during the week do so using more characters ($p < .001$) and words ($p = < .001$) than during the weekend. Further, these tweets typically express higher levels of anger ($p = .024$), whilst also using more auxiliary verbs ($p = .040$). Second, despite demonstrating higher levels of anger during the week, tweets are significantly more negative at the weekend ($p = .018$) with a corresponding increase in sad tweets ($p < .001$); related to this, there is also a marked increase in the expression of feelings during the weekend ($p = .010$).

5.3.2. Variations by Time of Day

Table 5 demonstrates differences in the content of tweets, based on the time of day that they are sent, broken down into 4-hour timeslots. There are notable differences based on the time of day that users are posting; midnight to 4am, for example, is the most negative time of the day (see Figure 3), with significant differences to every other timeslot, particularly 8am-noon, noon-4pm and 4pm-8pm (all $p < .001$). This same timeslot is also the most person-centred (see Figure 4), with the use of pronouns at the highest level within those 4 hours compared to the other timeslots; the most significant differences are with 8am-noon and noon-4pm ($p < .001$).

5.3.3. Variations between night and day

As demonstrated previously, and in Table 5, there is a general trend for values to differ in the night (i.e. 8pm – 8am) than during the day (i.e. 8am – 8pm). Here we compare these two time periods and demonstrate the level and significance of differences between the two.

In a similar finding to the previous weekend comparisons, tweets sent during the day contain significantly more characters ($p < .001$) and more words ($p < .001$). These daytime tweets also contain a higher amount of positivity ($p = .001$).

Tweets sent during the night, however, are much more negative than those sent during the day ($p < .001$), whilst also including a much higher use of pronouns, both personal ($p < .001$) and impersonal ($p < .001$), as well as being more focused on the present ($p < .001$). In conjunction with this, there is a higher prevalence of health-related words, and expression of feelings during the night.

5.3.4. Variations by Qualitative Theme

Previously we detailed the process by which the content of a subset of the data was qualitatively analysed, with content codes grouped and arranged into three over-arching themes: "Loneliness and Self", "Loneliness and Others", and "Irrelevant to Focus of Study". Table 6 shows the results of a quantitative linguistic content analysis of tweets falling into the two relevant themes, and the significance of the differences between the two.

There are notable differences between the two main themes of interest in this study. For example, tweets within the "Loneliness and Others" theme are significantly longer than "Loneliness and Self" tweets – both in terms of character count (p = .001) and word count (p = .002). Further, these tweets are more positive (p = .024) and focus more on the future (p = .039), as well as being more active, containing a higher proportion of verbs (p = .001). Conversely, "Loneliness and Self" tweets have a higher rate of 'sadness' in their content (p = .013)

6. Discussion

Here we discuss the overall findings of this study, with reference back to our original research questions, as well as implications that these may have in terms of informing future studies in this, or related, areas.

First, and in answer to our first research question, the results of our analyses demonstrate that individuals are utilising social media platforms, in this case Twitter, to disclose personal feelings of loneliness. This is not in itself surprising, and indeed has been highlighted by prior social computing research (Kivran-swaine et al., 2014).

However, we did note that disclosures vary in depth, from simple statements of *"I'm lonely"* through to more descriptive posts. Such disclosures highlight the potential usefulness of social media to individuals in such situations where they, by definition of feeling lonely, do not perhaps have friends and family in close proximity with whom they feel they can disclose their feelings, in an effort to help them. Further, this range of disclosure suggests that there may be individuals who begin by self-disclosing their loneliness through a simple statement, but over time, as network connections develop, and confidence in their online audience grows, may utilise social media for more in-depth self-disclosures in an effort to receive more support from others. Whilst our dataset only covers a 7-day period, a future study, conducted over a longer time period, may reveal users where this is the case.

Second, and in response to research question two, we have demonstrated that Twitter is being used as a reciprocal support network, with people not only stating *"I'm lonely"*, but also actively seeking out support, and providing support to other social media users. In some cases, this took the form of reciprocal self-disclosure (Pan et al., 2018), where users are sharing and discussing their own previous experiences of loneliness as a means of providing direct support to other users who are currently sharing their own feelings of loneliness. Further studies in this area, if conducted over a longer time period, may again demonstrate social media users whose behaviour changes and develops over time, as they receive support or positive response from their social media audience.

Research question three relates to the linguistic differences between our 'lonely' dataset and the control dataset. Our findings demonstrate statistically significant differences between the two. In particular, lonely tweets were more negative, using fewer characters, and expressing more anger.

This stark contrast between the two datasets demonstrates that discussions of loneliness on Twitter differ from the more general use of Twitter, particularly in terms of the language being used. This reinforces the findings of earlier studies, such as De Choudhury et al., (2013) and Kotikalapudi et al., (2012), which looked at utilising individuals' social media posts as indicators for symptoms of depression.

Fourth, the results of our quantitative linguistic content analysis, as well as the posts-per-day and posts-per-timeframe (see Table 1, Table 4, Table 5), demonstrate that user behaviour differs in relation to the time of day and day of the week; and in doing so, address research question four. Tweets sent at weekends and at night are generally shorter, sadder and more negative in terms of content, while making more references to feelings and emotions. With social sharing often occurring concurrently, or on the same day as a triggering event (Choi & Toma, 2014), this suggests that users may be making use of Twitter as a means of reflecting on their own feelings at that time, sharing how they are feeling lonely at the weekend – a period of time where, from a Western-centric viewpoint, it is more common to have time away from work or study and as such, socialising with others is perceived to be a cultural norm. In contrast to this, users are taking to social media during the week to post angry tweets related to loneliness

As such, future work should consider these behavioural patterns over a longer timeframe, and in relation to major calendar events and holidays, where feelings of loneliness might be assumed to be further exacerbated.

This demonstrates a need to consider the wider context (including time and day) where Twitter content is being posted. This further reinforces the findings of previous research (Ranney et al., 2016) that suggested that real-time monitoring of social media could be useful in predicting surges in visitor numbers to local emergency departments. While we are not suggesting that there are such correlations in our data, further studies could investigate this idea further, by analysing loneliness online over a longer period of time, and how user behaviour changes on a day-to-day basis, or in relation to specific calendar events that might normally infer social activity (such as national holidays or New Year's Eve).

7. Limitations

The work presented in this paper has some limitations that could be addressed in further studies. First, we only consider a single social media platform – Twitter. Disclosure and discussion of feelings of perceived loneliness is, of course, not limited to just a single social media platform. However, the affordances of Twitter are such that posted content may be broadcast to a much wider audience than, for example, Facebook. This may result in receiving replies and support from individuals who are not explicitly within a user's network of friends or followers. Second, we only consider content that contains the word 'lonely' – further studies should extend criteria to other words and phrases that might indicate users' disclosures of loneliness. Finally, the 7-day data collection period means that we were unable to study the development of individual users' behaviour over an extended time period.

8. Conclusion

In this article, we have examined the ways in which feelings of loneliness are articulated and self-disclosed on Twitter. In doing so, we contribute to the growing fields of work in this area; we highlight the importance of temporality to the expression of loneliness, linking it with periods when individuals may be most acutely aware of their lack of social or emotional support. This appears aligned to periods concordant with traditional periods of high social activity such as Friday nights and weekends. In contrast to this, Twitter appears to function not only as a platform to disclose feelings of being lonely, but functions to also facilitate extending support and allowing interaction with those disclosing feelings of isolation. Both this interaction, or the cathartic nature of expressing negative emotion may lead to a reduction in distress associated with low social contact. These findings invite a range of future research in social technologies, particularly those which function in real-time, as current disclosure of feeling lonely was prominent in our results.

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Day	# Tweets	Timeframe	# Tweets
Wednesday	3,466	Midnight – 4am	3,833
Thursday	3,068	4am – 8am	2,944
Friday	3,015	8am – Midday	3,446
Saturday	3,672	Midday – 4pm	3,540
Sunday	3,638	4pm – 8pm	4,166
Monday	2,652	8pm - Midnight	4,548
Tuesday	2,966		

Table 1. Number of tweets collected, by day and by timeframe.

Second-Order Theme	***First-Order Theme***	***Content Code***
Loneliness and Self	Fear & The Unknown	Fear of Being Lonely
		Personal Prediction of Future Loneliness
	Personal Disclosure	Personal Disclosure of Past Loneliness
		Personal Disclosure of Present Loneliness
		Personal Disclosure of Constant or Permanent Loneliness
		Personal Disclosure – Not Feeling Lonely
	Reflecting on Loneliness	Personal Thoughts or Comment on Loneliness
		Linking Loneliness to Love or Relationships
		Equating Loneliness with Being Single
		Humour or Sarcasm Relating to Loneliness
Loneliness and Others	Direct Support	Commenting or Sharing Opinion of 3rd Party Loneliness
		Supporting Others in Loneliness
	Indirect Support and Information Dissemination	Information & Factual
		Quotes Relating to Loneliness
Irrelevant to Focus of Study	Misuse or Misrepresentation of Loneliness	Vernacular for "by myself"
		Used as Part of an Insult or Abuse
	Irrelevant	Advert for External Resource
		Referencing Other Media – Lyrics, Videos etc
		'Lonely' is Part of Twitter Username
		Used when Describing Current Affairs / News / Politics etc
		Creative Writing / Fan Fiction
		Irrelevant or Inappropriate Content
		Unclear Meaning

Table 2. Hierarchy of content codes and themes.

Variable	Group Mean (Standard Deviation)		t	p	r
	Lonely Tweets	Random Sample			
Character Count	77.250 (38.460)	98.850 (46.542)	-51.352	<0.001	0.245
Word Count	14.100 (7.175)	14.120 (6.566)	0.661	0.508	0.003
Word Class					
Pronouns	13.665 (11.362)	3.820 (6.706)	106.381	<.001	0.509
Impersonal Pronouns	2.968 (5.171)	1.337 (3.671)	36.720	<.001	0.190
Verbs	15.541 (11.505)	5.230 (7.865)	105.617	<.001	0.490
Auxiliary Verbs	9.053 (9.350)	2.467 (4.890)	88.906	<.001	0.456
Sentiment Analysis					
Negative Sentiment	14.419 (13.507)	0.974 (4.137)	135.198	<.001	0.660
Positive Sentiment	2.908 (5.348)	2.795 (6.193)	1.975	0.250	0.010
Word Root Type					
Health	0.546 (2.508)	0.358 (2.043)	8.302	<.001	0.042
Feeling	1.629 (4.670)	0.294 (1.655)	38.281	<.001	0.236
Anger	0.851 (3.296)	0.276 (2.220)	20.629	<.001	0.110
Sadness	12.290 (12.330)	0.189 (1.829)	137.733	<.001	0.689
Anxious	0.614 (2.797)	0.304 (2.508)	11.808	<.001	0.059
Use of Tense					
Past Tense	1.568 (3.954)	1.010 (3.070)	15.843	<.001	0.081
Present Tense	12.227 (10.177)	4.237 (6.619)	93.902	<.001	0.452
Future Tense	1.095 (3.176)	0.457 (2.304)	23.208	<.001	0.120

Table 3. Comparison of quantitative linguistic content analysis results. All variables, with the exception of positive sentiment and word count, have statistically significant differences between the 'lonely tweets' dataset, and the random sample.

Variable	Lonely Tweets – Individual Days – Group Mean (Standard Deviation)						
	Wednesday	Thursday	Friday	Saturday	Sunday	Monday	Tuesday
Word Class							
Pronouns	14.112 (11.572)	13.779 (11.351)	13.759 (11.323)	13.328 (11.326)	14.015 (11.316)	13.265 (11.330)	13.278 (11.271)
Personal Pronouns	11.015 (10.316)	10.784 (10.047)	10.786 (10.031)	10.352 (10.132)	11.047 (10.109)	10.512 (10.093)	10.233 (9.893)
Impersonal Pronouns	3.082 (5.287)	2.984 (5.149)	2.956 (5.140)	2.971 (5.237)	2.966 (5.188)	2.741 (4.948)	3.033 (5.183)
Verbs	15.883 (11.433)	15.554 (11.435)	15.536 (11.394)	15.494 (11.638)	15.462 (11.543)	15.209 (11.784)	15.591 (11.304)
Auxiliary Verbs	9.348 (9.428)	9.115 (9.303)	9.254 (9.325)	8.828 (9.282)	8.889 (9.638)	9.043 (9.293)	8.931 (9.102)
Sentiment Analysis							
Negative Sentiment	14.020 (12.931)	13.983 (12.864)	14.301 (13.552)	14.741 (14.141)	14.745 (14.209)	14.826 (13.623)	14.286 (12.951)
Positive Sentiment	2.919 (5.341)	2.932 (5.199)	2.940 (5.432)	2.724 (4.983)	3.144 (5.689)	2.818 (5.270)	2.857 (5.263)
Word Root Type							
Health	0.501 (2.208)	0.630 (2.880)	0.476 (2.239)	0.549 (2.505)	0.548 (2.456)	0.539 (2.643)	0.583 (2.624)
Feeling	1.660 (4.441)	1.561 (4.476)	1.548 (4.362)	1.678 (4.843)	1.824 (5.042)	1.498 (4.489)	1.562 (4.887)
Anger	0.825 (3.267)	0.740 (2.993)	0.879 (3.345)	0.744 (3.095)	0.806 (3.423)	1.130 (3.709)	0.900 (3.251)
Sadness	12.009 (11.817)	11.875 (11.706)	12.105 (12.364)	12.801 (13.026)	12.656 (12.964)	12.520 (12.464)	11.946 (11.659)
Anxious	0.609 (2.834)	0.615 (2.688)	0.653 (2.874)	0.568 (2.721)	0.575 (2.723)	0.573 (2.693)	0.720 (3.046)
Use of Tense							
Past Tense	1.674 (4.093)	1.659 (4.057)	1.519 (4.007)	1.496 (3.857)	1.542 (4.005)	1.502 (3.844)	1.579 (3.781)
Present Tense	12.462 (10.230)	12.075 (9.990)	12.138 (9.999)	12.324 (10.406)	12.126 (10.201)	11.983 (10.456)	12.419 (9.913)
Future Tense	1.110 (3.090)	1.233 (3.402)	1.163 (3.407)	1.059 (3.066)	1.079 (3.236)	1.071 (3.080)	0.949 (2.919)

Table 4. Quantitative Linguistic Content Analysis Result, by Day. Changes in language use can be seen throughout the week.

Variable	Lonely Tweets – Time Blocks – Group Mean (Standard Deviation)					
	0-4h	4-8h	8-12h	12-16h	16-20h	20-24h
Word Class						
Pronouns	14.561 (11.481)	13.828 (11.731)	12.336 (10.954)	13.055 (11.240)	13.822 (11.374)	14.141 (11.299)
Personal Pronouns	11.425 (10.222)	10.712 (10.240)	9.592 (9.710)	10.288 (9.971)	10.776 (10.196)	11.107 (10.123)
Impersonal Pronouns	3.129 (5.318)	3.099 (5.435)	2.743 (4.918)	2.753 (5.011)	3.028 (5.128)	3.028 (5.211)
Verbs	16.671 (11.865)	15.491 (11.570)	14.087 (11.362)	14.975 (11.306)	15.745 (11.379)	15.985 (11.397)
Auxiliary Verbs	9.836 (9.860)	8.896 (9.330)	7.910 (8.831)	8.571 (8.910)	9.280 (9.504)	9.530 (9.395)
Sentiment Analysis						
Negative Sentiment	15.729 (14.616)	14.697 (13.419)	13.354 (12.695)	13.824 (13.514)	13.966 (12.626)	14.818 (13.856)
Positive Sentiment	2.767 (5.259)	2.941 (5.413)	3.419 (5.929)	2.828 (5.166)	2.890 (5.290)	2.695 (5.080)
Word Root Type						
Health	0.610 (2.929)	0.595 (2.574)	0.474 (2.184)	0.496 (2.303)	0.487 (2.371)	0.607 (2.583)
Feeling	1.772 (5.034)	1.718 (4.832)	1.457 (4.644)	1.541 (4.324)	1.579 (4.640)	1.694 (4.544)
Anger	1.025 (3.777)	0.917 (3.542)	0.740 (2.905)	0.760 (3.033)	0.813 (3.189)	0.849 (3.261)
Sadness	13.421 (13.486)	12.523 (12.259)	11.383 (11.537)	11.894 (12.562)	11.887 (11.378)	12.552 (12.513)
Anxious	0.559 (2.750)	0.643 (2.804)	0.616 (2.845)	0.609 (2.773)	0.680 (2.910)	0.584 (2.707)
Use of Tense						
Past Tense	1.543 (3.867)	1.637 (4.241)	1.377 (3.684)	1.680 (3.970)	1.614 (4.030)	1.558 (3.948)
Present Tense	13.062 (10.423)	12.202 (10.121)	11.102 (9.887)	11.683 (9.948)	12.438 (10.273)	12.619 (10.218)
Future Tense	1.218 (3.575)	0.996 (3.095)	1.015 (2.889)	1.049 (2.952)	1.137 (3.204)	1.112 (3.217)

Table 5. Quantitative linguistic content analysis results, by time of day. Changes in language use can be seen throughout the day.

Variable	Group Mean (Standard Deviation)		*p*-Value
	Loneliness and Self	Loneliness and Others	
Character Count	77.480 (38.673)	91.180 (36.162)	.001
Word Count	14.140 (7.220)	16.400 (6.707)	.002
Word Class			
Pronouns	12.693 (11.311)	15.983 (9.673)	.006
Personal Pronouns	9.874 (9.898)	12.239 (8.782)	.024
Impersonal Pronouns	2.819 (5.051)	3.744 (4.846)	.087
Verbs	14.940 (11.251)	18.688 (10.030)	.002
Auxiliary Verbs	8.056 (8.707)	10.556 (7.585)	.007
Sentiment Analysis			
Negative Sentiment	13.907 (12.616)	11.754 (8.165)	.031
Positive Sentiment	2.665 (5.071)	3.966 (5.375)	.024
Word Root Type			
Health	0.646 (3.316)	0.404 (1.494)	.463
Feeling	1.914 (5.635)	1.894 (3.903)	.972
Anger	0.640 (2.492)	0.940 (3.104)	.288
Sadness	12.129 (11.572)	9.245 (5.700)	.013
Anxious	0.385 (2.162)	0.419 (1.813)	.882
Use of Tense			
Past Tense	1.317 (3.595)	1.477 (2.840)	.667
Present Tense	11.863 (9.880)	15.125 (9.234)	.002
Future Tense	0.940 (2.860)	1.628 (3.920)	.039

Table 6. Quantitative linguistic content analysis, by qualitative theme. Differences can be seen between the two qualitative themes, for example – 'Loneliness and Self' containing more negative sentiment than 'Loneliness and Others'.

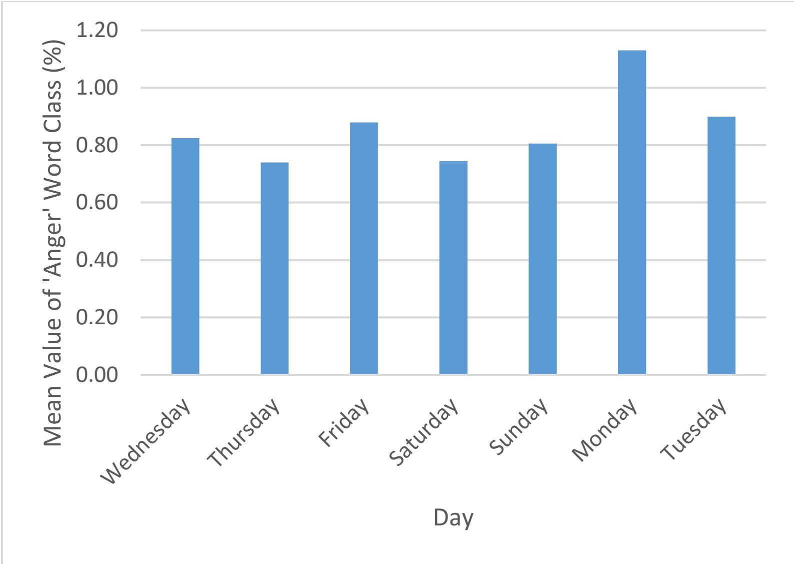

Figure 1. Mean value of 'Anger' word classes, per tweet, per day, showing Monday as the angriest day of the week.

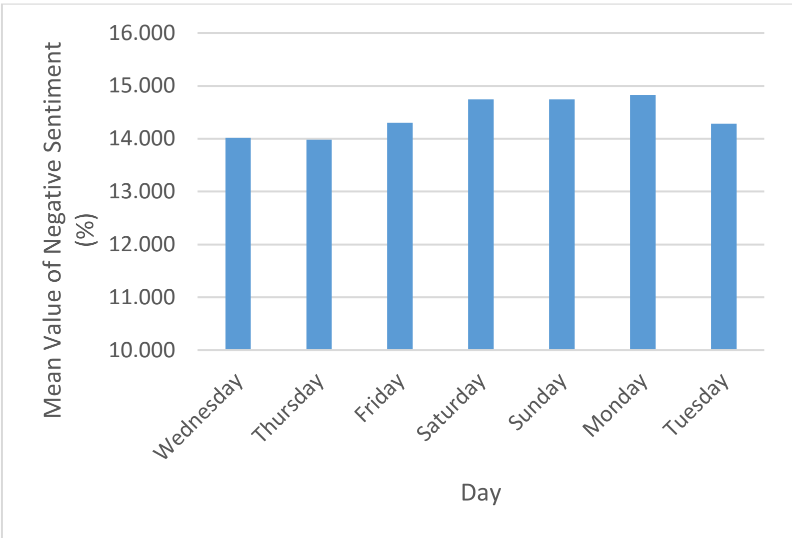

Figure 2. Mean value of negative sentiment per tweet, per day, showing Saturday, Sunday and Monday as far more negative than the rest of the week.

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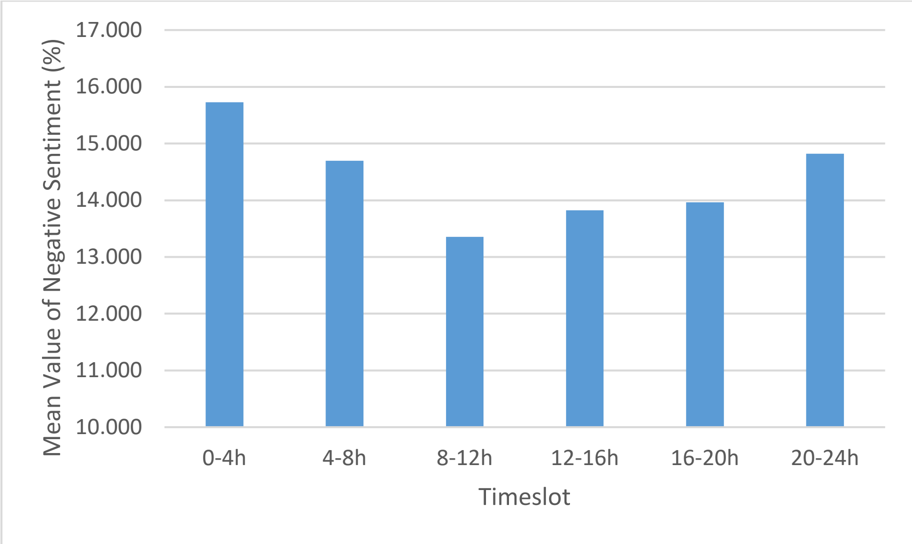

Figure 3. Mean value of negative sentiment per tweet, per timeslot, showing 0-4h as the most negative timeslot.

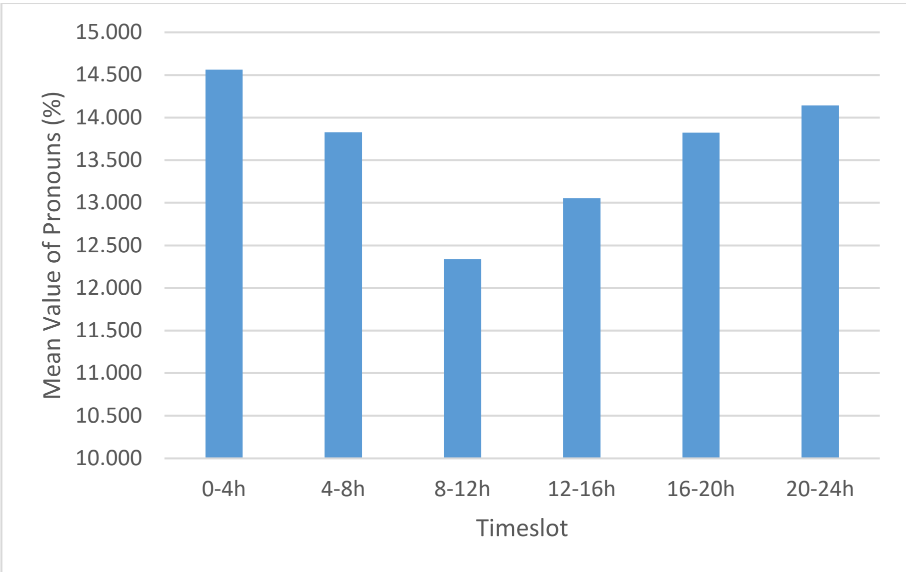

Figure 4. Mean value, 'Pronouns' per tweet, per timeslot, showing 0-4h as the most person-centric timeslot.